# Wind energy production backcasts based on a high-resolution reanalysis dataset

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## Abstract

Numerical weather prediction reanalysis data has been widely used in wind energy studies. Examples include large-scale wind resource analysis [1] and wind energy backcast simulations for electricity market integration studies. The success of such studies is highly dependent on the accuracy of the datasets used. The relatively coarse horizontal spatial resolution of many reanalysis datasets such as ERA-Interim (c. 80 km) limits their usefulness in such studies. The advent of high-resolution, country-specific datasets, such as Met Éireann's MÉRA reanalysis, allows for more detailed backcasts to be developed, with corresponding improvements in accuracy. The 2.5 km horizontal resolution of MÉRA, in combination with its previously-reported low bias compared to ERA-Interim 10 m wind speeds, makes it ideal for wind energy production estimation, as the spatial resolution is sufficient to resolve some terrain effects. In this study, we investigate the accuracy of wind energy production backcasts for a wind farm location in Ireland derived from MÉRA data. The results of various bias correction schemes are introduced, with the overall results showing good prediction accuracy even when relatively simple corrections such as the Kalman filter are applied.

## 1 Introduction

The power outputs of renewable energy sources such as wind are variable in response to changing weather conditions. Forecasts of wind generation are therefore useful in order to help system operators schedule and dispatch generators in order to balance supply and demand at all times, to help energy traders predict supply and price movements on electricity markets, and to assist wind farm owners to schedule maintenance outages for minimum loss of output [2, 3].

In recent years, as the proportion of total generation from variable, non-synchronous renewable energy sources such as wind and solar photovoltaics has increased, many new applications are emerging for accurate wind energy forecasts. For example, the increase in the penetration of renewable energy sources in many systems has led to electricity market reforms, including penalties for producing over or under the scheduled quantities. New hybrid wind-storage power plants have been deployed, and the owners of these assets have to make decisions on when to store energy and when to release energy when trading on futures markets. The elimination of payments to renewable generators for energy curtailed for operational reasons by system operators is a further motivation for more accurate forecasting of wind generation.

The increase in accuracy of numerical weather prediction (NWP) in recent years has led to a significant performance improvement in wind energy forecasting. The HARMONIE configuration of the ALADIN-HIRLAM model used by Met Éireann and other meteorological agencies runs with 2.5 km horizontal resolution mode, which allows for resolution of terrain and other influences on wind speeds which would not be possible in models with coarser spatial resolution. As the resolution of MÉRA is the same as that of the operational HARMONIE system of Met Éireann, using MÉRA as input to a wind forecasting system will: (1) provide a useful benchmark of the potential accuracy of HARMONIE, and (2) allow for the effect of model resolution on forecast accuracy to take place.

The aims of this study are therefore:

- To examine the accuracy of the new 2.5km horizontal resolution MÉRA dataset for wind energy backcasting.
- To identify appropriate forecast corrections to remove bias and improve forecast quality.

# 2 Data and methods

The chosen wind farm site is on relatively flat terrain in the midlands of Ireland, and has a site mean wind speed of 7.7 $\mathrm{m\,s^{-1}}$ at 100m above ground level according to the SEAI's wind atlas[1]). There are eighteen 2,000 kW turbines on the site each with a hub height of 95 m. Wind speed measurements from a meteorological mast on the site were supplied by the site operator.

We use horizontal wind speeds at the 10 m and 100 m levels from the MÉRA (Met Éireann ReAnalysis) dataset as inputs to our wind energy forecast model [4]. Interpolation of the discrete MÉRA grid cells to the target location of the

[1]SEAI wind atlas, http://maps.seai.ie/wind/

wind farm was achieved by fitting a weighted least squares combination of the four nearest grid cells (1,1; 1,2; 2,1; 2,2) to the target wind speed value $u_target$ (Eqn. 1).

$$u_{target} = a\, u_{1,1} + b\, u_{1,2} + c\, u_{2,1} + d\, u_{2,2} \tag{1}$$

Wind velocities at the 10 m level were initially provided by Met Éireann, and these were extrapolated to turbine hub height using the power law and an assumed shear coefficient value of $\alpha$=0.143. When 100 m wind velocities were released, these were used as inputs to the wind energy forecast. Prediction intervals of 3h and 24h were selected from the MÉRA dataset. Wind speeds at hub height were then transformed to wind generation time series by applying a speed-to-power transformation based on the turbine manufacturer's power curve. The power curve was scaled to match the wind farm's maximum export capacity. No attempt was made to incorporate the effects of turbine wake interactions or outages.

Historic generation output values at 30 minute time resolution were obtained from the Single Electricity Market Operator's website [2]. Local measurements of wind speed at 95 m height at ten-minute time resolution were also provided by the wind farm operator for the year 2016.

## 2.1 Data corrections

Several approaches were used in order to reduce the bias and other errors in the wind energy forecast model. A persistence correction was applied in the first instance. The purpose of the persistence correction was to provide a lagging bias correction, and to provide a simple benchmark correction against which to measure other, more sophisticated methods.

The next level of forecast correction was the application of threshold corrections on the persistence-corrected wind energy time series. Because the persistence correction is a lagging correction, it may lead to physically unrealistic output values (e.g. power values that exceed the capacity of the wind farm, or negative values). These were removed by employing a simple thresholding approach: where values exceeded the maximum export capacity of the wind farm, they were set to the maximum export capacity, and where values were negative they were assigned a value of zero.

The Kalman filter, a more sophisticated forecast correction method was then employed. The Kalman filter is an optimal estimator for linear dynamical systems [5]. "Optimal" in this case implies that the least squares prediction error is minimised. That makes it ideal for use in applications such as position estimation from noisy data, and bias correction of wind forecasts [6, 7, 8]. In this case, the Kalman filter was used to derive a state vector $\hat{x}(t)$ to minimise the bias in the forecast time series.

[2]Single Electricity Market Operator Dynamic Reporting Tool, http://www.sem-o.com/marketdata/Pages/dynamicreports.aspx

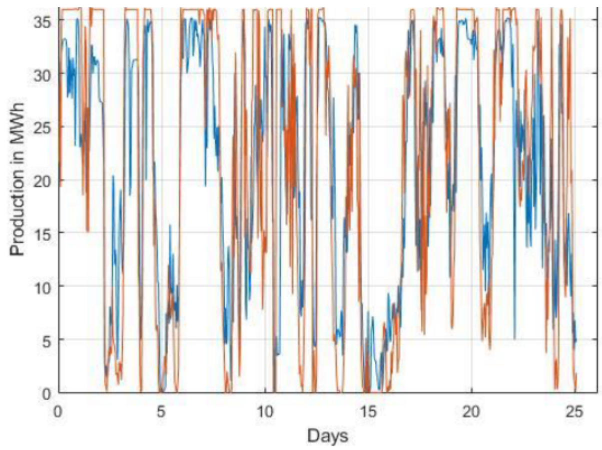


Figure 1: Wind generation forecast derived from "raw" MÉRA data (red) and actual generation values (blue) for February 2014.

Several error metrics were used to evaluate the performance of the forecasts, including: mean error (ME or bias); normalised mean absolute error (NMAE) and root mean squared error (RMSE).

# 3 Results

Sample time series of uncorrected and bias- and threshold-corrected wind generation forecasts are presented in Figs. 1, 2 and 3. The Kalman filter was applied to both wind power and wind speed time series, with better performance observed on wind speed time series (Fig. 3). The Kalman-corrected wind speed time series were subsequently transformed to wind power.

The results of a preliminary sensitivity analysis were used in order to determine the most sensitive parameters in the wind generation forecast model system. The influence on the prediction error of the shutdown of three turbines ("O&M"), 1% derating of the power curve, variation in value of shear exponent ($\alpha$) by 0.07, and of the choice of spatial interpolation (single nearest neighbour versus weighted combination of four nearest neighbours) to the target wind farm location ("downscaling") in Fig. 4. The results show that vertical extrapolation was the most sensitive factor examined in the analysis.

# 4 Discussion and Conclusions

Using the uncorrected MÉRA wind speeds for wind generation backcasting produces good results despite the simplicity of the wind energy forecast model. Fig. 1 shows that, even without any corrections to the raw MÉRA data, a simplis-

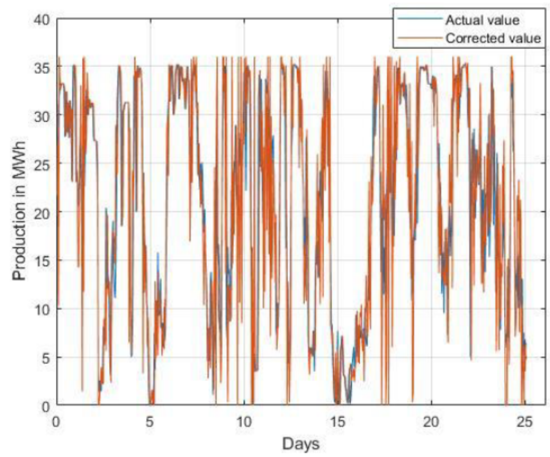


Figure 2: Wind generation forecast derived from persistence-corrected MÉRA data with threshold corrections applied (red) and actual generation values (blue) for February 2014.

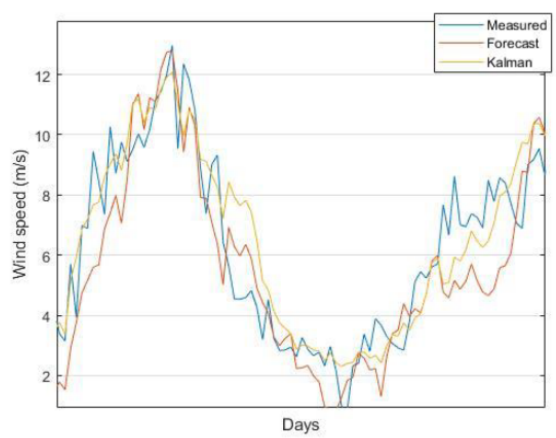


Figure 3: Wind speed forecast derived from MÉRA data with Kalman filter correction for January 2016.

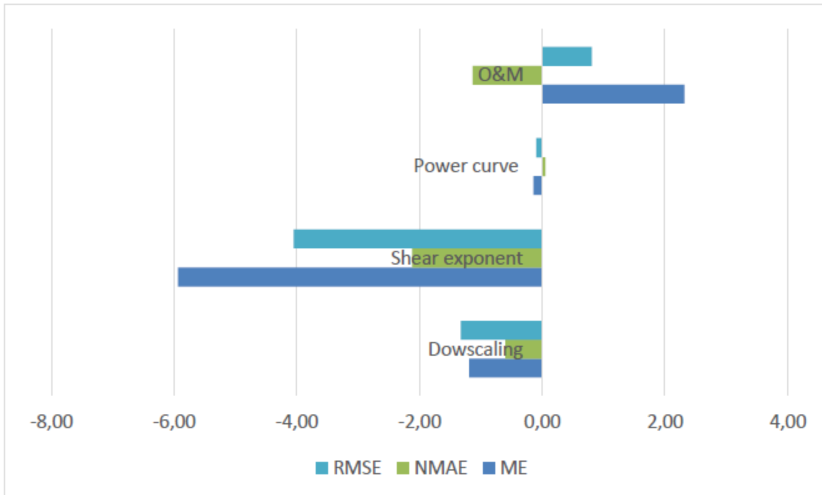


Figure 4: Sensitivity analysis of the wind generation forecast (% errors) to model parameters.

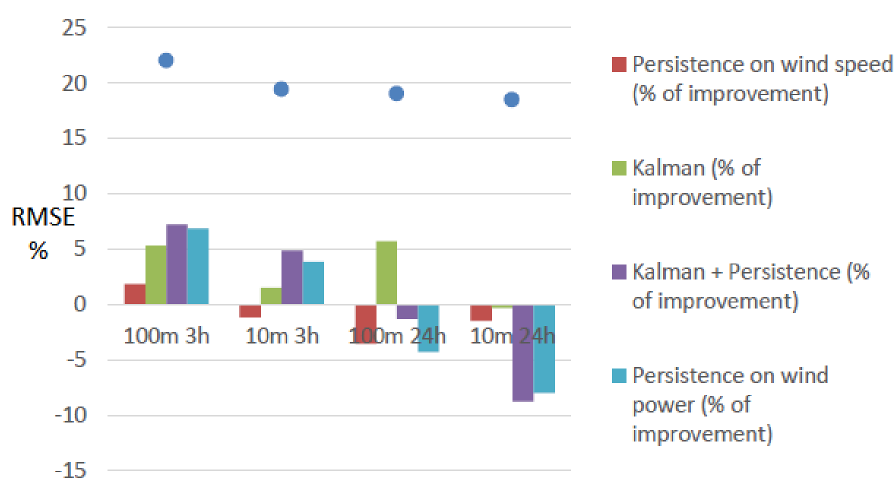


Figure 5: Improvements in root mean squared error over "raw" MÉRA-based forecasts for different prediction intervals (3h & 24h) and based upon 10 m and 100 m wind speeds .

tic speed-to-power conversion produces realistic values for wind farm generation output. This underlines the high accuracy of wind speeds in the MÉRA dataset. Application of relatively simple corrections (persistence and threshold cutoffs, Fig. 2) further improves the model performance, with a visible reduction in bias.

| Power output RMSE in MWh | | | | |
|---|---|---|---|---|
| | Raw | Pers | Pers + Thr | Kalman |
| **100m T+3h** | 7.94 | 5.48 | 5.20 | 6.04 |
| **10m T+3h** | 6.99 | 5.60 | 5.33 | 6.44 |
| **100m T+24h** | 6.84 | 8.38 | 6.88 | 4.78 |
| **10m T+24h** | 6.64 | 9.52 | 7.25 | 6.76 |

Table 1: Root mean squared error of wind energy forecasts derived from uncorrected ("raw") MÉRA wind speeds and from various corrections, for 10m and 100m wind speeds and 3h and 24h prediction intervals.

In general, the model performance is consistent across all error parameters used in this study, and in particular for the mean error. Forecasts for the T+3h prediction interval are only slightly more accurate than for the T+24h prediction interval. The Kalman corrected forecast based upon 10m data produces lower errors, especially much lower bias, than that based upon the 100m wind speeds. As expected, the Kalman filter is efficient at eliminating systematic bias such as that introduced by vertical extrapolation of wind speeds. This is also consistent with the results of the initial parameter sensitivity analysis. The performance of the various forecast corrections are summarised in Fig. 5 and in Table 1.

The Kalman filter applied to the NWP output produces good results across all error metrics, particularly in reducing the systematic bias. Thus, the Kalman filter efficiency depends more on the nature of the forecast errors than the overall accuracy of the forecast. Furthermore, access to the the measured wind speed data is key for good performance of the Kalman filter performance as these assist the model update step for bias correction.

The results of this wind energy generation forecasting exercise demonstrate that the accuracy of wind speeds from high resolution reanalysis data such as the MÉRAdataset should make such datasets extremely valuable in wind resource assessment. Further work will concentrate on more sophisticated corrections such as the extended Kalman filter which should further reduce the errors in wind generation forecasts derived from MÉRA wind speeds.

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